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RECOGNITION OF EYE MOVEMENT BASED ON BIOELECTRICAL SIGNALS USING NEURAL NETWORKS

The object of research is the process of generating and recording electrical signals caused by eye movements; the subject of research is the method of real-time recognition of eye movements based on these signals. It is implemented on the open VitalCore platform and uses a convolutional neural network (CNN) for real-time movement classification. One of the most problematic aspects is ensuring high accuracy with low power consumption and limited computing resources, as well as reducing the impact of noise and delay during signal processing. This is of particular importance when using the system in wearable devices and in real-world environments where signal quality may be unstable.

The study uses digital signal processing methods, in particular, filtering by the Savitsky-Goley algorithm, as well as architectural solutions in the field of neural networks: the use of a five-channel CNN with ordinary and transposed convolutional layers, Flatten and softmax. The use of frequent sliding windows (every 8 ms) is proposed, which increases accuracy and reduces latency.

The result is obtained: the recognition accuracy reaches 85% with a time window of 625–833 ms and a latency of about 40 ms, which provides the ability to detect up to five movements per second. This is due to the combination of an energy-efficient sensor with an optimized CNN architecture, which provides noise immunity and fast classification in real time.

Thus, the method allows to achieve stable and reliable results while maintaining low power consumption. Compared with known analogues, it is distinguished by openness, scalability, reproducibility and the ability to work on peripheral devices without high-performance computing resources. The development can be integrated into wearable devices and used in brain – computer interfaces, VR/AR, assistive technologies and medical research, which emphasizes its practical value.

***Keywords**: movements, eyes, QVar, windows, classification, signals, VitalCore, recognition, directions, gaze, sensors, learning.*

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1. Introduction

Eye movement recognition and monitoring of the state of the ocular apparatus is an important task in modern medical, rehabilitation and interface technologies. The problem of accurate, fast and energy-efficient detection of eye movements remains relevant on a global scale, since its solution opens up new opportunities for device management, diagnostics and therapy. Of particular importance is the development of solutions that work in real time, have minimal energy consumption and are convenient for use in portable and wearable devices.

In the context of Ukraine, this problem becomes particularly important due to the need to adapt technologies to local conditions: limited resources, specifics of the medical infrastructure and the needs of the population. This study addresses the task of eye movement recognition. Was use the example of objects and users in Ukraine. This helps to reflect regional application features. It also shows the potential for implementation in medicine and technology.

The study [1] presents a system for electromyographic (EMG) signal acquisition aimed at bio-controlled prostheses. It highlights the importance of reliable EMG signal processing for effective prosthetic control. However, challenges remain in filtering noise and ensuring signal stability during dynamic user movements, which complicates real-time application.

Research [2] focuses on signal acquisition tools for electroencephalographic (EEG) diagnostic systems, emphasizing hardware and software solutions for enhancing signal quality. Although effective in clinical EEG settings, the approach faces difficulties in adapting to portable or wearable systems due to power consumption and data processing requirements.

The educational manual [3] offers foundational knowledge in neurophysiology, providing insight into the physiological basis of bioelectrical signals, including EMG and EEG. While comprehensive, the resource primarily serves as a theoretical basis and does not address applied signal processing challenges.

Research [4] extends the understanding of neurobiology in development and learning processes, which can inform adaptive algorithms for signal interpretation. Yet, practical implementation of these biological insights in wearable sensor technologies remains limited.

Research [5] analyzes human EEG results and discusses signal processing techniques aimed at clinical diagnostics. The research underlines the need for high accuracy in signal interpretation but identifies constraints related to artifact removal and real-time responsiveness, which affect portability and user comfort.

Research [6] introduces a wearable and nearly invisible eye-motion monitoring sensor based on ferrofluid and electromagnetic sensing technologies. Their system achieves high accuracy (0.1°) and low

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latency (< 50 ms), offering a stealthy, autonomous solution. However, the necessity of special lenses limits widespread everyday use and increases cost and complexity.

Research [7] develops smart contact lenses for continuous, non-invasive eye health monitoring with wireless, multifunctional capabilities. While providing valuable long-term physiological data, these lenses face obstacles such as complex power supply requirements and limited operational resources, restricting their practical deployment.

Research [8] presents a soft optoelectronic device inspired by the human eye, using high-density MoS_2-graphene curved image sensor arrays. The device offers high resolution and sensitivity with biomimetic flexibility. Nevertheless, manufacturing complexity and dependence on external processors hinder scalability and integration into compact wearable devices.

Research [9] explores optoelectronic implants aimed at vision restoration, capable of basic object vision. The revolutionary nature of this approach holds significant rehabilitative potential. However, invasiveness and expensive surgical implantation limit accessibility and broader adoption.

Research [10] reports on multifunctional flexible contact lenses employing magnetic oxide nanosheets for eye health monitoring. Their biocompatible, wireless design represents an advancement in multifunctional wearable sensors. Despite this, the high cost and power supply miniaturization challenges present barriers to mass-market use.

Therefore, it is urgent to develop energy-efficient, reliable and user-friendly eye movement recognition m that can work in real time on wearable devices and are adapted to the conditions of Ukraine. This will allow the introduction of modern technologies in medical diagnostics, rehabilitation and human-machine interfaces, taking into account limited resources and the peculiarities of the local market.

Thus, *the aim of research* is to create a method of an eye movement recognition based on modern biosensors and neural networks, with optimization of power consumption and latency, adapted for use in mobile and wearable devices in Ukraine.

2. Materials and Methods

2.1. Data collection and processing methodology

The object of the research is the process of generating and recording electrical signals caused by eye movements. *Subject of the research* is the method of real-time recognition of eye movements based on these signals. The following scientific methods were used in the study. The analysis method helped to examine physiological features of the signals and existing processing algorithms. The experimental method provided empirical data during sessions with participants. The data collection method was implemented using the QVar sensor and the VitalCore platform. The filtering method, particularly the Savitzky-Golay filter, was applied to clean signals from noise. The segmentation method divided the continuous data stream into fixed time windows. The classification method based on neural networks (CNN) was used to recognize eye movement types. Finally, the supervised learning method allowed training the model on labeled data, which increased recognition accuracy. Each of these methods plays its role in building a reliable eye movement recognition system based on electrical signals.

Prior to the experiment, participants are instructed to sit approximately 60 cm away from the monitor. During the preparation phase, parameters such as the distance to the screen, ambient lighting conditions, and any additional comments or observations from the participant are recorded. To minimize the influence of unwanted signal artifacts, participants are advised to avoid unnecessary body movements and to refrain from blinking unless explicitly required by the task. Scheduled breaks are included throughout the session to reduce eye fatigue.

Each experimental session consists of five separate trials. A single trial comprises a sequence of instructions that are presented on the screen step-by-step. At the beginning of each trial, participants are asked to blink four times at one-second intervals, followed by maintaining gaze on the center of the screen for five seconds. This initial phase is essential for subsequent synchronization during data processing.

The dot on the screen then moves between eight different positions as shown in Fig. 1 – up, down, left, right, and all four corners – returning to the center each time. The interval between movements is one second. To mark instances of blinking, the word "Blink" appears at the center. To prevent predictability, the order of position appearances is randomized, with each position repeated twice per trial.

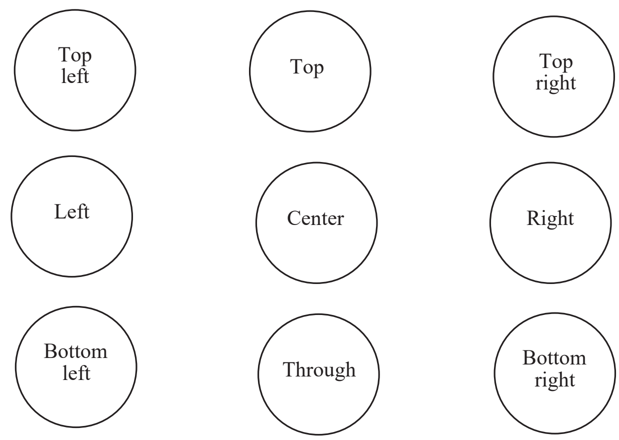

Fig. 1. Data collection positions

Thus, during a single session, each participant performs each type of movement ten times. The moments when instructions to perform movements are given are logged as markers using a logger.

2.2. Description of the data collection system

The signal acquisition is performed using the Qvar (Teva Pharmaceutical Industries Ltd., Israel) [1] LSM6DSV16X (STMicroelectronics, France, Italy) [2] sensor developed by STMicroelectronics. This device integrates accelerometer and gyroscope functionalities and is capable of conducting preliminary signal processing directly on the hardware. Equipped with an embedded amplifier, the sensor can detect weak electrical signals generated by eye movements.

The sensor includes two electrodes that capture, amplify, and transmit the signals to a microcontroller in digital format. Despite its low power consumption, full activation of the sensor may require up to 650 μA.

The entire system is built upon the open-source VitalCore1 [3] platform, which enhances reproducibility and facilitates straightforward scalability for further research. As illustrated in Fig. 2, the system architecture comprises three primary components: VitalCore, VitalPack, and the QVar sensor.

Fig. 2. System block diagram

The core component of the system is VitalCore, an open-access solution specifically designed for low-power consumption projects. This platform is based on the NRF534 [4] microchip.

For handling more computationally intensive tasks, the VitalPack module is utilized, featuring the GAP9 [5] chip from Greenwaves as its central processing unit. This energy-efficient microcontroller is designed to execute artificial intelligence algorithms directly on the device, i. e., at the system's edge. VitalPack is equipped with six connection channels, providing the system with high flexibility and enabling experimentation with various electrode placements.

Data exchange between VitalCore and VitalPack is conducted via direct memory access (DMA) and FIFO buffers, which enhances energy efficiency. VitalPack receives data from the QVar sensor, filters it, and transmits it to VitalCore. VitalCore segments the data into fixed time windows, which are then sent back to VitalPack for recognition processing. Subsequently, VitalPack transmits the recognition results to VitalCore for further use.

2.3. Description of the eye movement recognition approach

To develop a simple and lightweight algorithm capable of detecting eye movements while operating on a low-power processor, the Savitzky-Golay filter [6] and a convolutional neural network (CNN) [7] were employed. The acquired signals are divided into small segments (windows), which are subsequently standardized and smoothed using the Savitzky-Golay filter [8]

$$y_i = \sum_{j=-m}^{m} c_i \cdot y_{i+j}, \quad (1)$$

where y_i – smoothed value at point i, y_{i+j} – input values in a window of width $2m + 1$, c_j – filter coefficients (they depend on the order of the polynomial and the window size), m – number of points to the left and right of the central point (i. e. window size: $2m + 1$).

The processed data is fed into a CNN [9] for recognition. The network architecture is structured as follows: The first component is the input layer, which accepts data in the form of time windows with five channels corresponding to different sensors. This is followed by four 1D convolutional layers, each containing 64 filters with a kernel size of 7. After the convolutional layers, transposed convolutional layers (also known as deconvolution layers) are applied, each with 64 filters and a kernel size of 7, consisting of 7 channels. The next stage is a flatten layer, which converts the multidimensional data into a one-dimensional vector, preparing it for further processing in the fully connected layer. Subsequently, the data is passed through a fully connected layer, which links all neurons, enabling the model to calculate the probabilities for each class of eye movement based on the input data. The output layer utilizes a softmax function, which converts the results into probabilities. Each class receives a probability value that reflects the likelihood that the corresponding class is correct for the current eye movement.

During the training phase, the model is trained on pre-labeled data. Each data segment (window) is clearly marked with the exact start and end points of the eye movement. This ensures that the model knows that an eye movement is present within the window, and its task is to recognize which specific movement it is. This simplifies the task, as the model does not need to predict whether a movement is occurring – it is already confirmed. In some windows, there may be no movement at all. To prevent the model from assigning a random class in such cases, a special label, such as "no movement" or "blinking", is introduced. This helps avoid false positive predictions when no movement has occurred.

3. Results and Discussion

3.1. Optimization of the time window size

The eye movement recognition method is based on a 1D Convolutional Neural Network (CNN), specifically designed to process multi-channel time-series data acquired from eye movement sensors. The input to the model consists of pre-processed time windows. Each window contains five channels representing signals from different sensors. Prior to being fed into the network, the signals are smoothed using a Savitzky-Golay filter and standardized to zero mean and unit variance to reduce noise and normalize the data.

The architecture of the CNN begins with four 1D convolutional layers, each containing 64 filters with a kernel size of 7 and ReLU activation. These layers extract local temporal patterns from the multi-channel input signals. Following the convolutional layers, transposed convolutional layers (deconvolution layers) are applied, also with 64 filters and a kernel size of 7, producing 7 output channels. This upsampling improves temporal resolution while preserving the extracted features.

Next, a flatten layer converts the multi-dimensional feature maps into a one-dimensional vector suitable for the fully connected layer. The fully connected layer links all neurons and calculates the probabilities for each eye movement class. The final output layer uses a softmax activation function, producing a probability distribution over all classes, including directional eye movements, blinking, and no movement.

The model is trained using supervised learning on windows that are pre-labeled with the exact start and end points of eye movements. Windows with no movement or blinking are assigned a special label to prevent false positives. The network is optimized with the Adam optimizer and uses categorical cross-entropy as the loss function. Performance is evaluated via cross-validation, ensuring that the reported accuracy reflects the generalization capability of the model.

This CNN-based approach allows for real-time recognition of eye movements while maintaining a lightweight architecture suitable for low-power processors. The combination of optimized window size, pre-processing, and multi-channel convolution enables the system to achieve high classification accuracy and reliable detection of various eye movements.

The duration of the time windows used for segmenting the signals has a significant impact on the recognition accuracy of the CNN model. To determine the optimal window size, a series of experiments were conducted in which the model was trained and evaluated using different time window durations. The performance was measured using 5-fold cross-validation, ensuring that the reported accuracies reflect the model's generalization ability rather than overfitting to specific data segments.

Time windows ranging from 625 to 833 ms, corresponding to 150–200 data points at a sampling rate of 240 Hz, were found to provide the highest classification accuracy, around 83–85%. The mapping between the window duration and the number of points is determined directly from the sensor's sampling frequency, ensuring these numerical values are consistent and reproducible.

For comparison, a standard window of 416 ms (100 points) resulted in slightly lower accuracy (81%), while shorter windows led to a notable drop in performance: 208 ms (50 points) achieved 64%, and 104 ms (25 points) only 44%. In addition, a larger window of 1042 ms (250 points) was also tested. Its accuracy (83–84%) was very similar to the optimal window, indicating that extending the window beyond the optimal range does not significantly improve performance, but still captures sufficient temporal information.

The results are presented in Tables 1–3 and in Fig. 3, where each fold is a separate test set on which the accuracy of the model is evaluated.

Table 1

Small window (208 ms, 50 points)

Fold	Up (%)	Down (%)	Left (%)	Right (%)	Blink/no movement (%)
1	62	63	64	65	64
2	63	65	64	66	64
3	64	63	63	64	65
4	64	64	65	63	64
5	63	64	63	64	63
Average	63.2	63.8	63.8	64.4	64.0

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Table 2

Optimal window (729 ms, 175 points)

Fold	Up (%)	Down (%)	Left (%)	Right (%)	Blink/no movement (%)
1	85	84	83	84	83
2	84	83	85	82	83
3	85	85	84	83	84
4	82	83	82	82	83
5	84	84	83	84	84
Average	84.0	83.8	83.4	83.0	83.4

Table 3

Large window (1042 ms, 250 points)

Fold	Up (%)	Down (%)	Left (%)	Right (%)	Blink/no movement (%)
1	84	83	83	83	83
2	83	84	84	82	83
3	84	83	83	83	84
4	82	83	82	83	83
5	83	84	83	84	83
Average	83.2	83.4	83.0	83.0	83.2

These results demonstrate that windows that are too short do not contain enough information for reliable classification, whereas windows within the 625–833 ms range capture sufficient eye movement dynamics to maximize model performance. With this optimized window size, the system can detect up to five eye movements per second, exceeding the typical frequency of natural human eye movements (approximately 3–4 movements per second). Therefore, the selection of the window size is both empirically justified and physiologically meaningful.

3.2. Evaluation of recognition speed

To assess the speed at which the model detects eye movements, a "sliding window" method was employed. In this approach, the data are divided into short segments of 416 ms (100 data points), which partially overlap, with a new segment starting every 8 ms. This method ensures that no movement is missed, even if it occurs at the boundary between windows.

For each movement occurring at a specific moment, the first window begins slightly earlier to fully capture the initiation of the movement. The system then progressively shifts the windows forward in time, and for each, the model attempts to determine whether a movement is present and, if so, its type. This approach allows for the assessment of when the model "recognizes" the movement.

If the model correctly identifies a movement, the delay is calculated as the difference between the movement's onset time and the moment the model provides the correct response. This methodology simulates the real-time conditions under which the system operates.

During testing, it was found that only 1% of movements went undetected. The majority of movements were correctly identified before they were fully completed, with the median delay being just 40 ms. This delay is approximately the same duration as the movement itself. Additionally, it was observed that shorter movements, such as upward or downward movements, were detected more quickly due to their shorter physical duration.

3.3. Real-time performance evaluation

During the real-time experiments, data were processed using a sliding window approach, where each window contained 100 data points (416 ms) with a step size of 8 ms. The model demonstrated the ability to correctly classify over 89% of eye movements, indicating its high reliability. On average, the delay in recognizing an eye movement was 40 ms, which is comparable to the typical duration of the eye movement itself.

Table 4 compares the results of technologies for eye movement detection, eye health monitoring, and vision-related applications.

Thanks to the combination of Savitzky-Golay filter and CNN, it was possible to achieve a high accuracy of 89% with a recognition delay of approximately 40 ms. This puts the development on a par with advanced developments, in particular with the approach [6], which also demonstrates fast and accurate tracking of eye movements, albeit through a different physics – ferrofluid.

Unlike contact lenses [7, 10], the development does not require direct contact with the surface of the eye, which reduces the requirements for biocompatibility and allows avoiding invasive intervention. At the same time, the development works with external sensors, which may be less convenient in terms of user comfort in everyday wear.

Compared to [8], which developed a curved visual sensor based on nanomaterials, the development has lower complexity in manufacturing and greater openness of the platform, which makes it attractive for research and educational use.

Compared to optoelectronic implants [9], the development is much less invasive and allows for comparable delay, without surgical intervention.

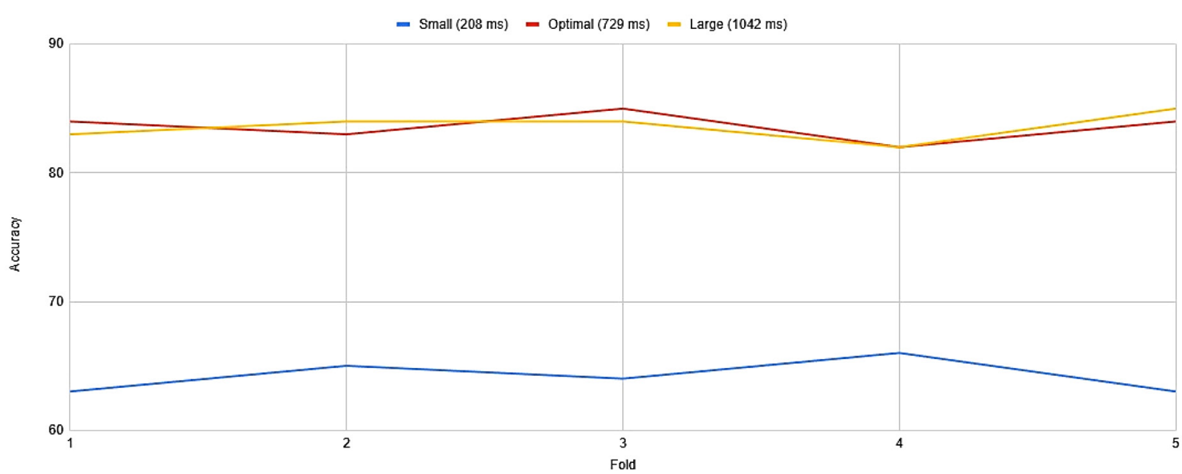

Fig. 3. Average accuracy for different window sizes

Table 4

Comparison of results

No.	Source	Technology	Goal/objective	Results	Advantages	Disadvantages
0	Own research	QVar + CNN on VitalCore	Eye movement recognition (non-invasive)	Accuracy 89%, latency ~ 40 ms	Real-time, low power consumption, open source	Requires fixed position, external sensor, model training
1	[6]	Ferrohydrin + EM sensors	Eye movement monitoring	Accuracy 0.1°, latency < 50 ms	High accuracy, stealth, autonomy	Requires special lenses
2	[7]	Smart contact lenses	Long-term monitoring of eye physiology	Continuous bio-data collection	Wireless, multifunctional	Complex power supply, limited resource
3	[8]	MoS_2 – graphene sensor	Vision simulation	High resolution, sensitivity	Flexibility, biomimicry	Production complexity, need for an external processor
4	[9]	Optoelectronic implants	Vision restoration	Basic object vision	Revolutionaryness, impact on rehabilitation	Invasiveness, expensive implantation
5	[10]	Magnetic nanolayers in the lens	Eye health monitoring	Multifunctional lens	Biocompatibility, wireless exchange	Expensive, requires miniaturization of power supply

The practical significance of the results is the possibility of using the developed system for highly accurate and fast recognition of eye movements in real time with minimal delays. This opens up broad prospects for implementation in various areas, such as bio-controlled interfaces for people with physical disabilities, attention control systems and eye health monitoring, as well as in virtual and augmented reality to increase control accuracy. Due to the low power consumption and open architecture of the platform, the system can be used in portable or wearable devices, which increases its practical value for a wide range of applications.

3.4. Limitations of the study and directions for future development

The limitations of the study are related to the need for a fixed position of the sensors relative to the user's eyes, which may reduce comfort during prolonged use. In addition, the external placement of the sensors makes the system less convenient compared to contact solutions such as smart lenses. For wider implementation, it is necessary to improve the adaptability of the system to various physiological characteristics of users and increase the stability of operation during dynamic changes in the position of the head or environment. It is also necessary to take into account possible sources of signal artifacts and develop methods for their automatic elimination.

Prospects for further research include the development of adaptive machine learning algorithms that can take into account the individual characteristics of users and change during the operation of the system. It is also advisable to integrate the system with other sensor devices to expand functionality and increase recognition accuracy. The development of more compact and comfortable hardware solutions, as well as research into the impact of different operating conditions on signal quality will be important steps for commercialization and widespread implementation of the technology in medical, rehabilitation and consumer devices.

4. Conclusions

The obtained results confirm the feasibility of combining energy-efficient hardware with lightweight neural architectures to ensure reliable classification in real-world conditions.

The distinguishing feature of the proposed approach lies in the integration of a Savitzky-Golay filter with a five-channel CNN and the use of frequent sliding windows (every 8 ms). This combination provides a balance between accuracy, latency, and computational efficiency. As a result, the solves part of the general problem of creating energy-efficient, noise-resistant, and real-time signal processing methods for wearable devices and brain – computer interfaces.

Unlike invasive or contact-based technologies, the system ensures non-invasive recording, scalability, and openness of implementation while maintaining low power consumption.

The effectiveness of the method can be explained by the optimal selection of signal segmentation windows in the range of 625–833 ms, which best capture the dynamics of eye movements, and the CNN architecture optimized for time-series analysis, which ensures both high precision and fast decision-making.

In quantitative terms, the model demonstrated:

– 83–85% accuracy for window sizes of 625–833 ms versus only 44–64% for shorter windows;
– the ability to detect up to five eye movements per second, exceeding the natural physiological rate (3–4 per second);
– 89% overall accuracy in real-time experiments with a median recognition latency of ~ 40 ms;
– less than 1% of movements left undetected during testing.

Conflict of interest

The author declares that he has no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The research was conducted without financial support.

Data availability

The manuscript has no associated data.

Use of artificial intelligence

The author confirms that he did not use artificial intelligence technologies when creating the presented work.

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